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ABSTRACT

A two-year study that attempted to measure patterns of pupil attributions for success and failure in mathematics is reviewed. An attribution pattern variable (ATTPAT) was created to categorize individuals studied into three groups. The first group had an attribution pattern thought to lead to generalized low expectancies for success. Students classified as "high" were in the second level of ATTPAT, and pupils placed in the third level were those who could not be categorized within either of the first two groups. It was found that a student's perceptions about how others viewed him constituted important causal variables in both years of the study. Interest in and the rated importance of mathematics by students was heavily affected by performance in the second year of the study only. In general, the results and analysis indicated that notions about the functions of attribution patterns may need to be seriously revised. Factors identified as calling for further study include more explicit specification of hypotheses, models, and predictions about the causal role of attributions, with particular regard to the direction and magnitude of effects. Neither the grade level of the students nor the mathematics being studied is specified. (MF)

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CAUSAL ANALYSIS OF EXPECTANCIES
AND VALUES CONCERNING MATHEMATICS

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Early in their careers, social scientists learn that correlation is not causation. For instance, two variables which covary may be implausibly causally related--e.g., shoe size and intelligence. Cook & Campbell (1979) have described several necessary-but-not-sufficient criteria which can be used to aid the scientist in making causal inference. These criteria include: 1) covariation of variables (variables in a presumed cause-effect relation must be related), 2) temporal precedence of cause over effect (to establish causality, an effect cannot precede the variable presumed to cause it), and 3) the need to use 'control variables' to rule out rival hypotheses. This criterion is advanced in recognition of the fact that fallacious inferences can be made about possible cause-effect relations. The notion of spurious correlation, for example, describes the case where covariation between two variables, say mortality rates and length of time married, is due to their joint dependence on a third variable--in this case, age.

In the randomized experiment, the researcher can manipulate events so as to meet these criteria for the inference of causality. The experimenter controls the covariation of independent variables and their temporal sequence, and attempts to rule out rival hypotheses by eliminating confounding variables through the design of the study. Random assignment of subjects to conditions insures the equivalence of treatment and control groups prior to the experimental manipulation. Experiments tend to have high internal validity--that is, the validity or 'truth' of statements about causality is maximized by their use.

While randomized experiments may be highly desirable in terms of internal validity, non-randomized field studies are often undertaken

when randomized experiments are impractical, unethical, or undesirable. Non-randomized field studies often have the advantage over randomized experiments in terms of external validity. External validity refers to the validity or truth of statements about the generalizability of causal relationships across alternate measures of the cause and effect and across different types of persons, settings, and times. Although it is true that threats to internal validity are more numerous and severe in non-randomized field studies, this does not mean that valid causal statements cannot be revealed by such studies. There is a greater need to rely on statistical or theoretical criteria to infer causation in these studies than in experiments.

Path analysis refers to a set of statistical techniques for making causal inference first described by Wright (1934) and developed for social science applications by Duncan (1966) and others (Blalock, 1971). In path analysis, causal parameters are estimated through the use of sets of multiple regressions. A path coefficient is the name given to the standardized regression coefficient or Beta weight used in ordinary least squares regression (OLS). The path coefficient is an estimate of causal effects of one variable on another represented in terms of the standard deviations of these variables. Although path coefficients are commonly used in the path analysis literature, only path regressions will be employed in this paper. Path regressions are the unstandardized OLS (multiple) regression coefficients or b weights. Theoretical and practical considerations justify the exclusive use of unstandardized path regressions in this research.

Certain statistical and theoretical assumptions must be made to use path analytic techniques. First: path analysis assumes an additive or

linear model. As in OLS regression, errors in equations are assumed to be uncorrelated with each other. Treatment groups are assumed to have equal variance and all variables are assumed to be measured without error. When these assumptions are met, then path analysis leads to efficient and unbiased estimates of causal parameters.

Equally or more important, path analysis requires theoretical assumptions to be met. Specifically, the researcher must determine the sequence of OLS regressions in an a priori fashion. If achievement, for example, is thought to be determined by attitude, then achievement must be regressed on attitude and not vice-versa. The important assumption to be met is the assumption that the model tested is specified correctly. Specification error refers to the degree to which the mathematical representation of the theory diverges from reality--that is, how inaccurate the theory is. The greater specification error, the more biased are the estimates of the causal effects. Researchers often use the statistical convention of $p \leq .05$ to make decisions about meaningful paths.

The Expectancy/Value Model of mathematics attitudes and choice behavior which we have offered (Parsons, Putterman, Goff, Kaczala & Yeece, Note 1) specifies the manner in which causes and effects in this domain are presumed to operate. Thus, this model was used to determine the sequence of path regressions. The construct of attributions about achievement outcomes occupies a central role in our model, but how is the importance of attributions to be assessed? One solution would be to enter into the regression equation each of the 18 attributional explanations for success and failure which students were required to rank in importance. This data analysis assumes simple additivity of

attributional effects, while several authors have suggested that it is the pattern of an individual's attributions for success and failure outcomes that is important. Therefore an attribution pattern variable (ATTPAT) was created. ATTPAT was used to categorize individuals into three groups. This categorization depended on the pattern of their rankings of different attributions for success and failure on a hypothetical math test. Students classified in the first level of ATTPAT (low) responded to the attribution measure with an attribution pattern thought to lead to generalized low expectancies for success. This pattern is characterized by internal attributions for failure and external attributions for success. Students classified in the second level of ATTPAT (high) responded to the attribution measure with an attribution pattern thought to lead to generalized high expectancies for success. This pattern is characterized by internal attributions for success and external attributions for failure. Students classified in the third level of ATTPAT were those students in neither the first nor the second level.

Having created this nominal variable, it was necessary to transform it by dummy variable coding for regression purposes. It has been demonstrated that the unstandardized regression weights of dummy-coded variables can be summed to determine the direct effect of the decomposed variable on the dependent variable (Lyons, 1971).¹ To examine the impact of including a variable representing the effects of the attribution process, the entire sequence of regressions was run twice, once with and once without the dummy variables. The R^2 values

¹The summation is over $N-1$ of the dummy variables, where N is the number of levels of the decomposed variables; i.e. the N th level is constrained to be zero.

(variance-accounted-for) are compared for each dependent variable in each of these models. The researcher must then make a judgment about the size and/or meaningfulness of any differences in R^2 values.

Separate ATPAT variables and ATPAT dummy variables were created for each year of the two-year study, and separate path analyses were performed for each year of the study. This allowed two tests of our model. The results of the path analyses are shown in Figures 1 and 2. The lines in these figures represent path regression coefficients statistically significant at the $p \leq .05$ level. Path regression coefficients in both figures are the estimates of causal parameters when ATPAT is included in the model. Paths to and from ATPAT are not drawn, since it is not possible to determine correct standard errors for the decomposed variable. Several variables included in the path analysis at year one have been deleted from the year two path analysis. Including these variables would have drastically reduced the number of subjects available for path analysis.

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Insert Figures 1 & 2
- - - - -

One's perceptions or significant others' judgments about self were found to be important causal variables in both years of the study. For instance, perceptions of others' judgment about self's ability had a significant impact on current expectancies, task difficulty judgments, and perception of one's current performance (which here included self-concept of ability). Judgments of the effort of math for self were a significant cause of judgments about the utility, importance, and worth of mathematics. Sex of child had a consistent effect on utility and on future expectancies as well. One interesting discrepancy is in the

causal centrality of the performance variable in years one and two of the study. Interest and importance were both affected by performance in Year two, whereas no significant causal role was found for performance in Year one of the study.

Examining the R^2 values of the models which include and exclude ATPAT, the results are discouraging to the expectancy/value model we have propounded. The total effect of ATPAT is consistently small, ranging from 3% to 6% of variance accounted for in year one, and from 0% to 4% in year two. Using a phrase borrowed from Duncan & Featherman (1973), we ask ourselves if this improvement is "substantively non-trivial". Because of these discouraging findings, the analyses were rerun, using year two dependent variables and the year one ATPAT classification, in an attempt to see if the first year pattern classification had greater causal impact on second year dependent variables than did the Year two classification of ATPAT. This was not the case. The difference in R^2 values was no greater in this analysis than in the previous analyses. In fact, the year one ATPAT occasionally acted as a suppressor variable. We must conclude that support for our model is not forthcoming from this set of analyses.

Perhaps this set of results indicates that our model is misspecified. Were this the case, the path analytic estimates of the causal effect of attributions may have been biased. Rather than rely on our model to specify the "correct" representation of cause and effect relations among attitudinal variables, the technique of cross-lagged panel correlation (CLPC) was used to help make causal inferences. CLPC aids in the inference of causality by examining the pattern of correlations of two variables measured at two different points of time.

The essential notion of CLPC is that the correlation of a cause measured at time 1 with its lagged effect should be greater than the correlation of an effect measured at time 1 with its cause measured at time 2. The difference between the values of these cross-lagged correlations is tested, and causality is inferred if this difference reaches statistical significance. There are several theoretical assumptions to be satisfied. These assumptions are known as stationarity and synchronicity (for a full discussion of this technique, see Kenny, 1975). The null hypothesis of CLPC assumes common-factoredness--that is, covariation observed between variables is due to their dependence upon a third variable.

Kenny's PANAL program was used to compute these analyses. Attitude scales included in this analysis were those scales on which there were sufficient data both years of the study. Only subjects with non-missing data on all these scales were included because of the suggestion that this procedure increases the stability of the observed correlation ($N=255$).

CLPC examines all pairs of input variables for cross-lagged differences. Current practice holds that uncorrected correlations not be used in CLPC. The pattern of significant cross-lagged differences can be schematically represented in the form of a path diagram (Figure 3). Examining this diagram, one sees that perceptions of the future difficulty of math and the perceptions of its worth seem to cause expectancies, interest, utility of math, and self-concept of ability.

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 Insert Figure 3
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This diagram does not include attributions, however. The importance of attributions was assessed using path analysis on the CLPC-derived model and including the ATTPAT variable. Only variables which were found to be either causes or effects using CLPC were included in this path analysis. As above, path analysis was carried out as two sequences of path regressions, one of which included ATTPAT, and one of which did not include this variable. Separate path analyses were run for each year of the study.

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 Insert Figures 4 & 5
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Results of these analyses show that more variables are implicated in causal relationships than would have been thought using CLPC alone. Some of the causal relations revealed by CLPC are not found using path analysis, but this result may be due to the fact that the data were analyzed within each year of the study rather than between years. Comparing the sequence of regressions including ATTPAT with those not including ATTPAT, attributions were not found to account for a large amount of variance in most dependent variables. There is a single exception to this statement: attributions account for a large amount of variance in one's current expectancies for success in math. The increase in R^2 is approximately 9% in both years, and seems "substantively non-trivial".

These results raise some questions for attribution theory in general and our model in particular. It is possible that these findings are due to the nature of the ATTPAT variable. If untransformed ratings

of attributions were entered into the regression equations, perhaps results would differ considerably. However, the relative paucity of variance accounted for by the ATPAT variable indicates that notions about the functions of attribution patterns may need to be seriously revised. This revision should result in more explicit specification of hypotheses, models, and predictions about the causal role of attributions, particularly with regard to the direction and magnitude of effects. For instance, are attributions a cause or an effect of attitudes? Should they impact on expectancies or on values; or perceptions of self vs perceptions of others vs perceptions of tasks; or on future orientations rather than assessment of current state? We intend to address ourselves to these questions in the future.

Reference Notes

1. Parsons, J., Putterman, R., Goff, S.B., Kaczala, C.M., and Meece, J. Expectancies, values, and academic choices: Origins and change. In J.T. Spence (Ed.), Assessing achievement. San Francisco: W.H. Freeman, in press.

References

- Bialock, H.M., Jr. (Ed). Causal models in the social sciences. Chicago: Aldine, 1971.
- Cook, T.D. and Campbell, D.T. Quasi-experimentation: Design and analysis issues for field settings. Chicago: Rand-McNally, 1979.
- Duncan, O.D. Path analysis: sociological examples. American Journal of Sociology, 1966, 72, 1-16.
- Duncan, O.D. and Featherman, D.L. Psychological and cultural factors in the process of occupational achievement. In A.S. Goldberger and O.D. Duncan (Eds.). Structural equation models in the social sciences. New York: Seminar Press, 1973.
- Kenny, D.A. Cross-lagged panel correlations: A test for spuriousness. Psychological Bulletin. 1975, 82, 345-362.
- Lyons, M. Techniques for using ordinal measures in regression and path analysis. In H.L. Costner (Ed.) Sociological Methodology, 1971. San Francisco: Jossey-Bass, 1971.
- Wright, S. The method of path coefficients. Annals of Mathematics Statistics, 1934, 5, 161-215.

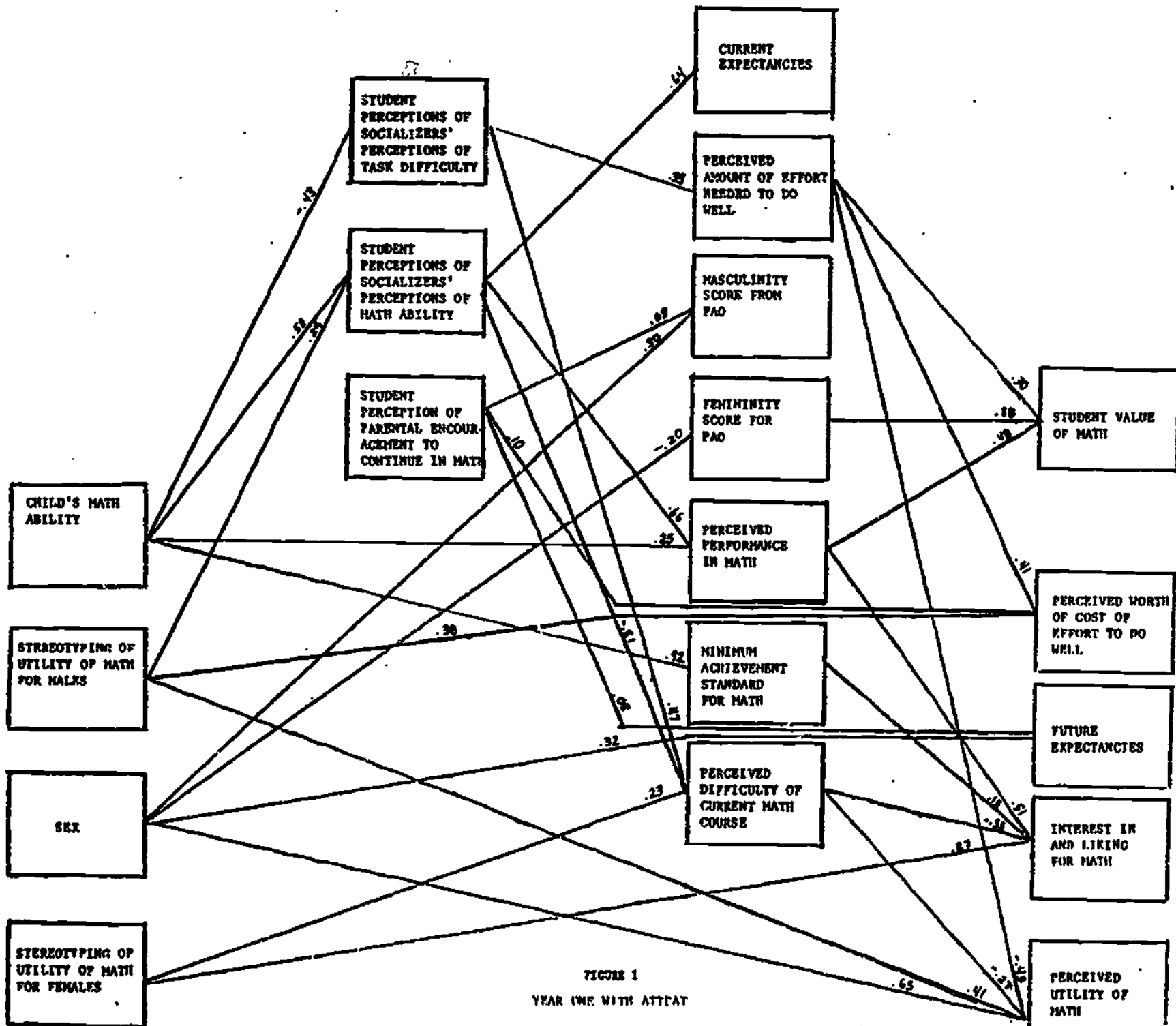


FIGURE 1
YEAR ONE WITH ATTEND

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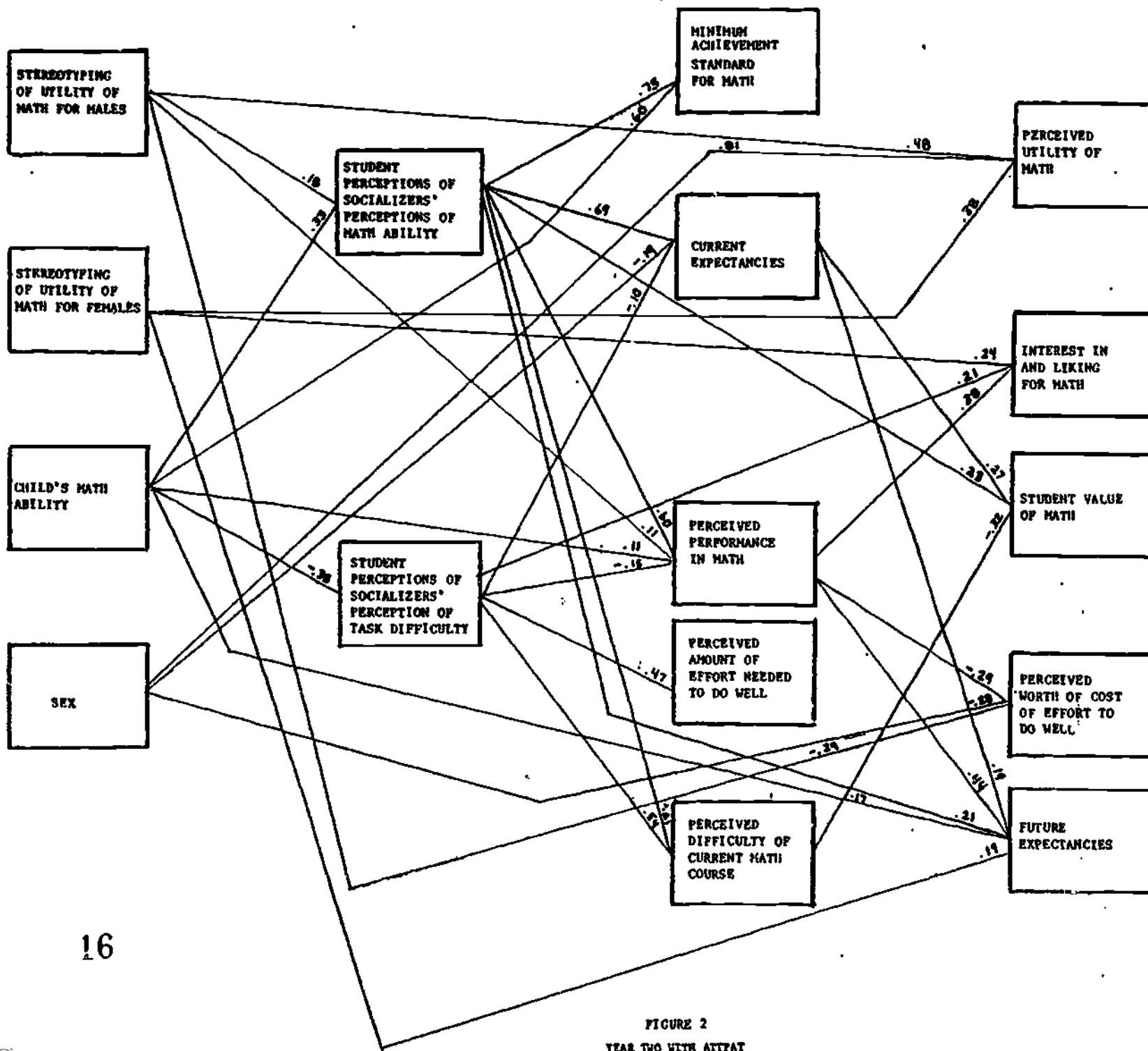


FIGURE 2
YEAR TWO WITH ATTPT
ALL PATHS $p < .05$

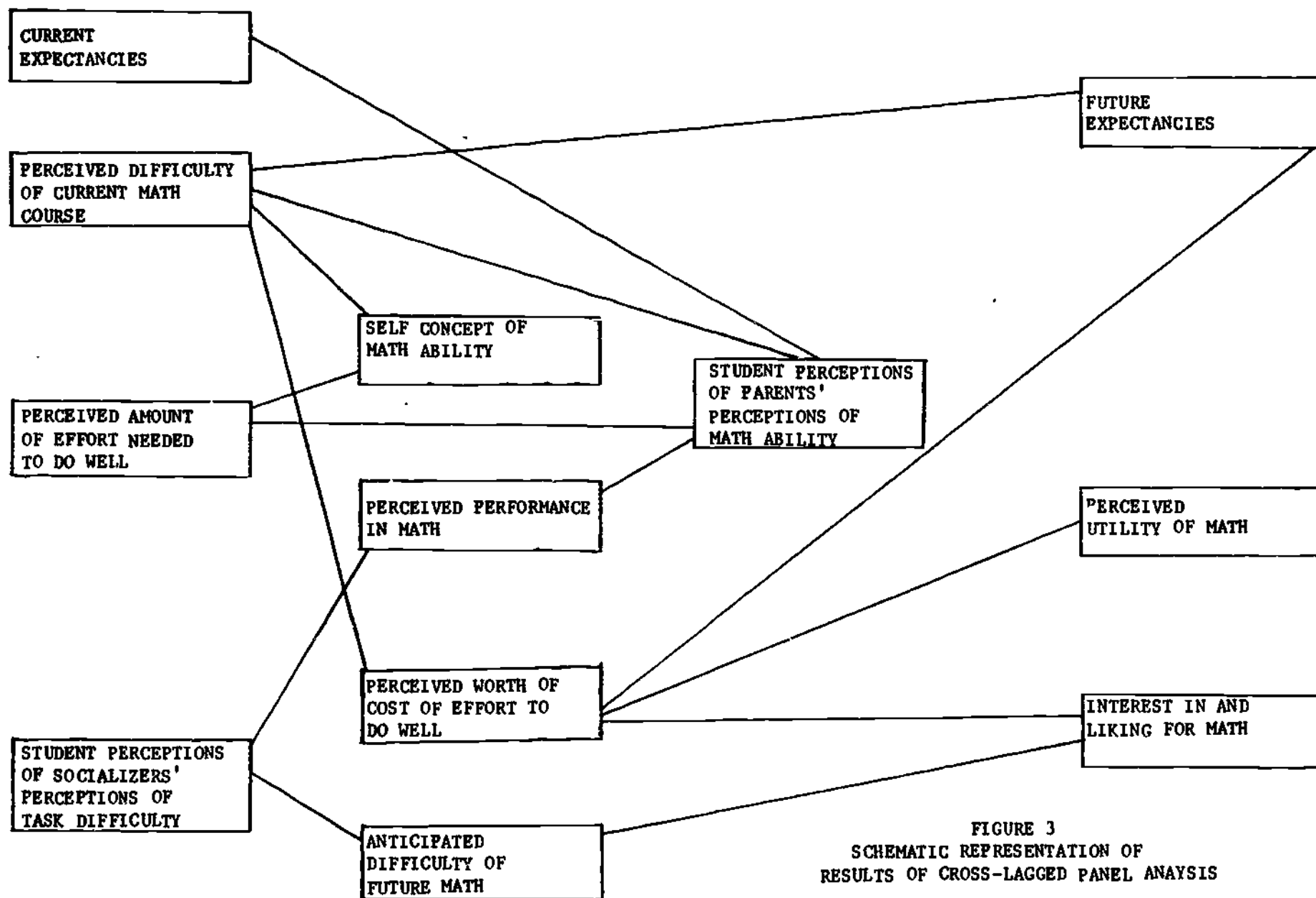
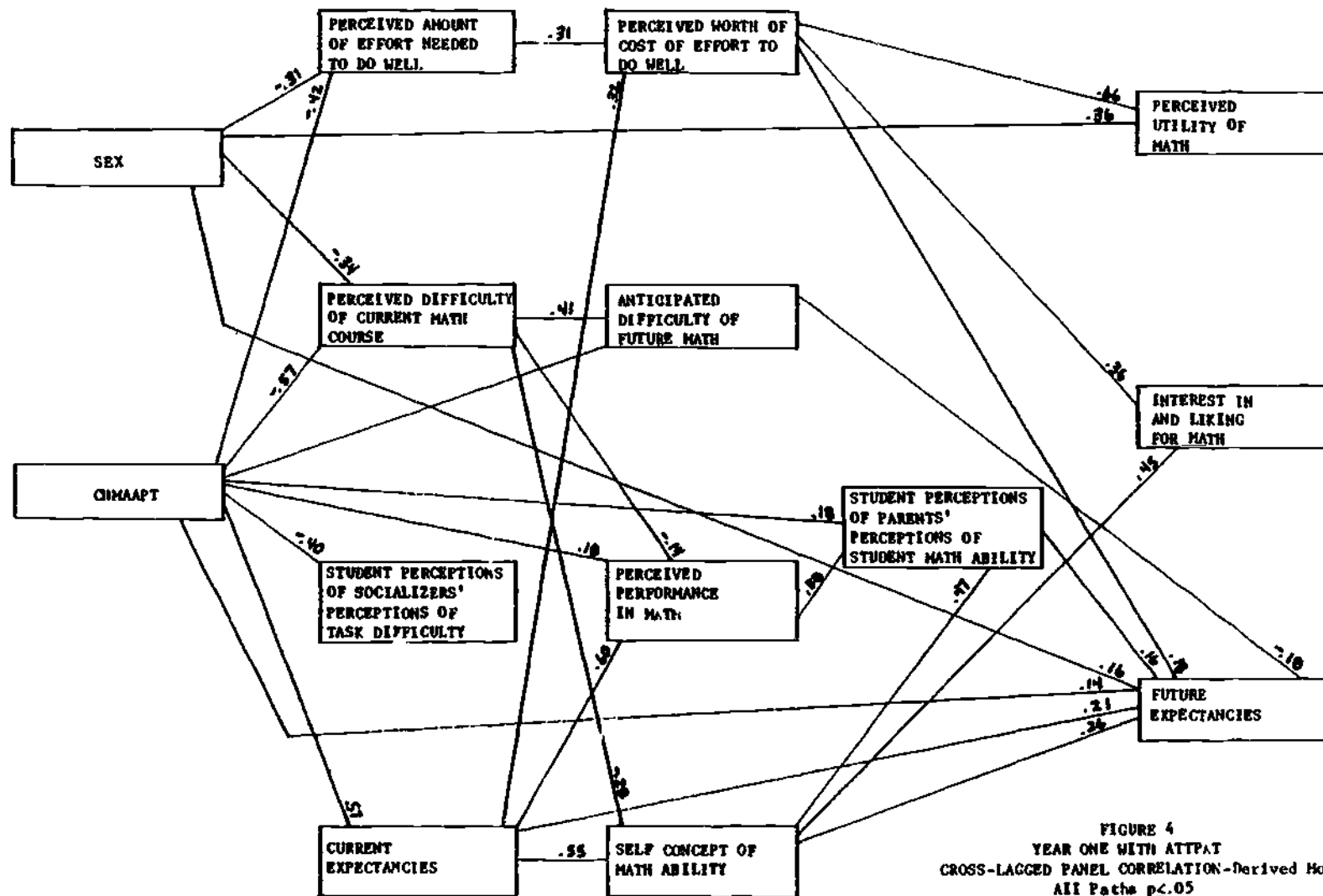


FIGURE 3
SCHEMATIC REPRESENTATION OF
RESULTS OF CROSS-LAGGED PANEL ANALYSIS



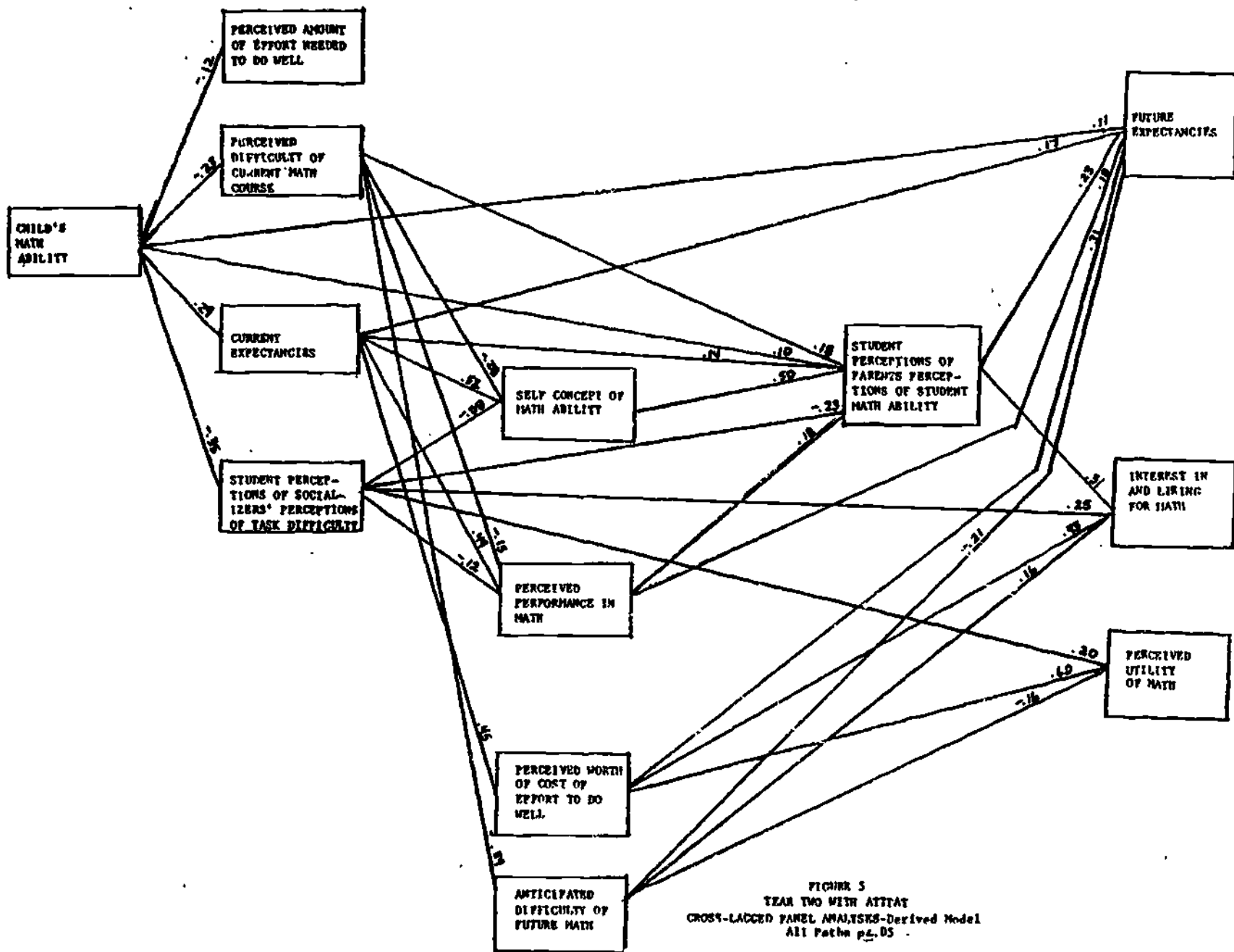


FIGURE 5
 YEAR TWO WITH ATTITUDE
 CROSS-LAGGED PANEL ANALYSIS-Derived Model
 All Paths $p < .05$